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Integrating intuition and artificial intelligence in organizational decision-making

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Abstract Artificial intelligence (AI) is fundamentally changing organizational decision-making processes. With the abilities to self-learn and to improve decision quality, AI is now taking over many decision responsibilities that were formally assigned to humans alone. However, the effectiveness of AI for ill-structured and uncertain decision environments is still in question. In such decision contexts that have no precedent on which to base a solution, humans have historically relied on their intuition to make decisions. Yet intuition, too, has been found to have weaknesses that restrict decision quality. Therefore, this article introduces a decision-making model that effectively integrates the strengths of both intuition and AI while minimizing the vulnerabilities of each method. The model specifies when and how both modes should be combined for effective organizational decision-making. In addition, the article presents important future research considerations relating to AI for both practitioners and academics.

1. Intuition or artificial intelligence?

With the advent of advanced technology such as machine-learning and artificial intelligence (AI), organizational decision-making has reached a new era. These technologies have fundamentally altered organizational processes and have significantly affected individual and organizational information processing and decision-making. Today, with the aid of artificial neural networks with deep learning models (Schmidhuber, 2015), not only can vast amounts of data be analyzed almost instantaneously (Shrestha et al., 2019), but with more data input, the AI systems can learn and improve decision-making (Miller & Brown, 2018). These abilities to self-learn and to improve decision quality, rather than relying on explicit instructions by humans, have made AI the next frontier in technology.

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Thus far, AI is most effective in predictive decision environments where there is enough historical data to forecast future outcomes (Tambe et al., 2019). However, the ability of AI consistently to make accurate decisions in environments of uncertainty is still in question, especially when there is no precedent on which to base a decision. Organizational decision makers have often relied on their intuition to make decisions in such environments with a high level of uncertainty and time pressure (Agor, 1986; Burke & Miller, 1999). Consequently, there has been much debate as to the efficacy of intuition as contrasted with more analytical forms of information processing and decision-making (Kahneman & Klein, 2009).

Although scholars have often contrasted intuitive versus analytical decision-making and attempted to identify which method is more effective (e.g., Dane et al., 2012; Pretz, 2008), little research has explored how intuition and analysis can work together to make optimal decisions. Herbert Simon (1957), a pioneer in the study of intuition and AI in decision-making (Frantz, 2003), understood the importance of this collaboration when he wrote, "It is a fallacy to contrast analytic and intuitive styles of management" (Simon, 1987, p. 63). Especially considering today's AI technology, which offers extreme analytic and interpretive capabilities, it seems prudent for organizational and management research to explore optimal ways intuition and analysis can be combined to improve organizational decision-making.

To this end, the purpose of this article is to introduce a model for combining human intuition and AI to improve organizational decision-making. The article first presents a short review of both intuition and AI and then discusses when and how both forms can be integrated to enhance decision quality. As technology changes at an extraordinary rate, traditional decision-making models may become less relevant and useful. Therefore, from an academic research perspective, examining and understanding how human capabilities can be matched and combined with new technology will give rise to new theories and more applicable decision-making models. For practitioners, advanced technology, especially AI, has fundamentally changed organizational processes and, at the same time, increased the anxiety among humans that their jobs will be taken over by cyber systems. Finding effective ways to integrate humans and AI will therefore not only optimize organizational decision-making but also take a step toward alleviating a greater societal concern.

2. When is intuition useful?

The concept of intuition has intrigued management and psychology scholars for decades. Chester Barnard (1938), one of the first management scholars to emphasize the role of intuition in managerial decision-making, identified intuition as a rapid, nonlogical, and complex decision-making process. Intuitive decisions often are referred to as judgments based on gut feelings (Shapiro & Spence, 1997). In the mid-20th century, emphasizing the role of intuition in organizational decision-making, Herbert Simon (1957) concluded that owing to the overwhelming amount of available information in real-world situations and the limited capacity of the human brain to process that information, individuals tend to rely on intuition. He called this phenomenon bounded rationality. The underlying assumption of bounded rationality is that because of information-processing deficiencies of the mind, humans are limited in their ability to make optimal, or even satisfactory, decisions in complex environments (Simon, 1992).

Simon's (1957) argument implies that intuition is a default method to make decisions in complex decision-making environments. But not all research has embraced intuition as a valid mode of decision-making. For example, Kahneman and Tversky's (1973, 1983) seminal work on heuristics and biases portrays intuition as a flawed form of judgment owing to three forms of biases Akinci & Sadler-Smith, 2013):

- *representativeness*: similarities with prior situations;
- *availability*: what comes easily to mind; and
- *anchoring*: what comes to mind first.

Diverging from the heuristics-and-biases view and offering a more positive view of intuition, the naturalistic decision-making framework emerged in the late 1980s (Lipshitz et al., 2001). The naturalistic decision-making framework highlights the usefulness of intuition by focusing on the role of expert intuition (Klein, 1993; Klein et al., 1986, 1989). According to this view, in complex real-world settings (e.g., when goals are ill-defined and tasks are ill-structured; when there is uncertainty, ambiguity, and missing data; or when under time stress), analytical techniques are not always feasible or effective (Klein & Klinger, 1991). In these types of settings, owing to extensive experience in the decision-making domain, an expert is instead able to recognize the correct course of action without much deliberation (Klein et al., 1986). Consequently, intuition is now considered an effective mode of decision-making when the decision maker is a domain expert and when the task is ill-structured (Dane & Pratt, 2007).

3. Expert intuition

As argued by supporters of the naturalistic decision-making view and as evinced by existing research (e.g., Dane et al., 2012), expertise in the decision-making domain is a necessary condition for the effectiveness of intuition. Domain expertise refers to the amount of knowledge and experience the decision maker has in a particular field. For example, a chess grand master is a domain expert in the game of chess. Domain expertise has been found to lead to effective intuitive decisions (e.g., Chase & Simon, 1973; Dane et al., 2012; Dijkstra et al., 2013; Hammond et al., 1987). But the effectiveness of an expert's intuitive judgment is restricted to their domain of expertise (Dane & Pratt, 2007). Therefore, an individual who is an expert in one domain may not be able to make an effective intuitive decision in a completely different domain. Relatedly, the intuitive judgments of novices are ineffective owing to their lack of domain-relevant knowledge (Dane et al., 2012).

4. Ill-structured tasks

In addition to domain expertise, the other necessary condition for the effectiveness of intuition depends on task characteristics. When dealing with problems that are conducive to analytical solutions, analytical decision-making may be best. However, when dealing with problems that are ambiguous and ill-defined, intuitive decision-making may well be a better option (Denhardt & Dugan, 1978; Friedman et al., 1985; Hammond et al., 1987; Hogarth, 2002). Tasks that are conducive to analytical solutions, also referred to as intellective tasks (Dane & Pratt, 2009), are highly decomposable (Hammond et al., 1987) and can be solved using reason or mathematical formulas. In such decomposable tasks, an individual can analytically solve the problem and articulate or illustrate the steps taken to derive the solution. Given these characteristics, intuition may not be effective for decomposable tasks (Dane et al., 2012). Analytical tools such as AI appear to be better than humans in solving such decomposable tasks.

In contrast, intuition is effective for complex and ill-structured tasks that are not as easily decomposed (e.g., Dane et al., 2012; Dijksterhuis, 2004). Unlike decomposable tasks, these types of tasks are abstract and are difficult to solve using math and logical inference. As a result, for ill-structured tasks, also referred to as judgmental tasks (Hammond et al., 1987), it is difficult to derive a solution using a purely analytical process. Therefore, for such tasks, intuition may be more effective, as the intuitive process allows the individual to make holistic judgments by considering the different aspects of the task that cannot be combined using an analytical method. In fact, managers generally prefer intuition for unstructured tasks where there is no clear objective method to solve the problem (Hodgkinson et al., 2009).

5. AI in organizational decision-making

AI is defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 15). Put more simply, AI is intelligent machines that can think, learn, and make decisions accordingly. A distinguishing feature of AI systems from other computerized systems is that, similar to the human intellect, these nonhuman entities can not only absorb and process information but also learn and update their decisions based on new information. In essence, these artificial systems are made to mimic the processes of the human brain, hence the term "artificial intelligence."

The concept of AI is believed to have originated in the mid-20th century (Haenlein & Kaplan, 2019) but has recently gained much prominence in both academic and industry circles. A historic event that marked the emergence of AI as a game changer in the modern era is the much-publicized IBM Watson's performance in Jeopardy (Jarrahi, 2018). In another landmark event, AlphaGo, an AI program developed by Google, defeated the world champion in go, which is a board game that is argued to be substantially more complex than chess (Haenlein & Kaplan, 2019).

The extreme capabilities of AI are rooted in advanced computational programs that are developed through artificial neural networks and deep learning models. Artificial neural networks are adaptive computational models that use numerous algorithms to make complex nonlinear associations within substantial datasets (Miller & Brown, 2018). Deep learning is an advanced form of artificial neural network that uses multiple layers of processing to learn hierarchical representations of data (Young et al., 2018). For example, in image recognition, by using prior data to learn the characteristics of a particular image type, a program based on an artificial neural network will be able to recognize and classify a new image (e.g., a human face). A deep learning program, on the other hand, can extract more in-depth information that enables a deeper understanding of the image (e.g., determining the emotional state of an individual through recognizing facial expression patterns).

AI has fundamentally changed not only organizational processes but also the roles humans play in organizations. Over the last few years, capabilities of AI have progressed from repetitive tasks to analytical tasks and now to thinking tasks, taking on more of the responsibilities that previously were assigned to human intelligence. As a consequence, humans are increasingly assigned to managing the interpersonal aspects of a business that AI has not yet mastered (e.g., communicating with internal and external stakeholders, conflict resolution), thus giving rise to the "feeling-economy," in which most human jobs may become primarily relational (Huang et al., 2019).

AI is used for various types of organizational tasks. For example, recent developments have seen a surge of AI in predictive tasks, such as forecasting weather based on past weather patterns (Agrawal et al., 2019). This advancement in predictive technology certainly aids human decision-making, as decision makers are now better able to compare the potential outcomes and risks associated with decision alternatives. Furthermore, and marking a significant breakthrough in technology, there is evidence that AI can even be effective in environments that have imperfect information, the type of environment generally prevalent in an organizational decision-making context. For example, DeepStack, an algorithm developed for imperfect information settings, uses deep learning methods to derive a judgment similar to human intuition to estimate the value of cards held by opponents in games of poker. By doing so, DeepStack has been able to defeat professional poker players at a statistically significant level (Moravčík et al., 2017). As poker is the epitome of a context with imperfect and asymmetric information, the success of DeepStack is an indication of how AI can be used in dynamic and competitive business environments, where managers often have to make important decisions based on imperfect information.

6. AI concerns

The proliferation of AI in organizational processes has simultaneously raised several concerns. For example, various concerns are relevant in the use of AI in the field of human resources (HR). These include the high complexity of HR problems, small data sets, ethical and legal constraints, and employee reactions to AI (Tambe et al., 2019). The complexity of HR largely revolves around the difficulty in assessing what constitutes a good employee and the interconnectedness of jobs that makes it difficult to separate an individual from group performance. For example, even with AI technology, it is difficult to accurately measure intangible attributes, such as an individual's contribution to positive team morale.

In terms of the small data set issue, AI is reliant on extensive data input to facilitate machine learning. Nevertheless, there may not always be enough historical data to allow AI to make accurate predictions. For example, past employee data may not be available for a job role that is new to the organization. Ethical and legal considerations are typically the result of privacy issues surrounding the increased gathering, storing, and usage of employee data. Lastly, due to the skepticism about decisions made by algorithms (Dietvorst et al., 2018), employees may have a negative reaction toward AI-based decisions, especially if those decisions have an adverse impact on the employees (Tambe et al., 2019).

The challenges of AI assimilation to organizational decision-making are not unique to the HR function. Many organizational problems, especially those involving interpersonal issues, are intricate, with nuances that are not readily assessed even with advanced computing. Lack of relevant historical data to guide future decisions, ethical and legal considerations, and negative employee reactions to decisions made by computers rather than humans are all concerns that need to be overcome to use AI in organizational settings effectively.

7. Similar concerns between AI and intuitive decision-making

Some of the issues of decision-making using AI are not dissimilar to concerns with human intuitive decision-making. For one, human intuition often is characterized as prone to individual biases (Akinci

Table 1. A case for integrating expert intuition and AI: Real-world examples

Risks of AI overdependence without human collaboration	At its outset, Amazon's free same-day delivery service received backlash for discriminating against largely minority neighborhoods. Amazon used an algorithmic system to decide in which areas to offer this service. The company claimed that race was not a consideration in the calculations and that the decision was based on a cost-benefit analysis (e.g., the number of Amazon Prime members in the ZIP code, distance from the nearest Amazon warehouse). But the areas that were excluded from this service had a majority African American population, likely because most Prime members lived in predominately Caucasian neighborhoods. As a result, Amazon was heavily criticized and later expanded the service to some of the previously excluded areas (Ingold & Soper, 2016).
	In a study conducted by ProPublica in Broward County, Florida, the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), an algorithm-based computer system used by the U.S courts to estimate the likelihood of recidivism, was found to be biased against African American defendants. Although skin color was not a factor considered in the calculations, other factors, such as the crime rate in the defendant's neighborhood, may have inadvertently biased the system against those of a certain race (Angwin et al., 2016). Although Northpointe (the company that developed the software) disputed the ProPublica analysis, the findings highlight the grave consequences if decisions are made solely based on the risk scores derived from such computer systems.
	Watson for Oncology, an AI-based program developed by IBM to generate treatment recommendations for cancer patients, has come under criticism for not delivering as promised. The program was developed to improve clinical decision-making by analyzing vast amounts of medical literature and patient health records. Although Watson learned how to scan published clinical studies and to gather statistics about the main outcomes, the program could not be taught how to extract information the way a physician does. As a result, the recommendations were not as useful, which has hindered the adoption of the program in clinical care (Strickland, 2019). The inability of an advanced AI system such as Watson to match the inferring capabilities of a human expert stresses the importance of combining human expertise with AI.
Successful AI and human collaboration	An AI-based recruiting system used by Unilever attempted to combine human and AI capabilities to increase the efficiency and effectiveness of the company's recruiting process. The AI-based system was used in the first two rounds of selection to determine candidate traits (e.g., risk aversion), capabilities, and suitability to specific positions. Depending on the AI's judgment, the best candidates were then invited for in-person interviews, where human decision makers made the final hiring decisions. The collaboration resulted in broadening the scale of Unilever's recruiting, with increases in both the overall number of applications as well as the socioeconomic diversity of applicants. Also, recruiting speed increased from 4 months to 4 weeks, while the time recruiters spent reviewing applications decreased by 75% (Wilson & Daugherty, 2018).
	As part of a Defense Advanced Research Projects Agency (DARPA) program, researchers at the Harvard Medical School collaborated with an AI-based system to identify the reasons why a powerful melanoma drug lost its effectiveness in helping patients after a few months. The researchers followed an iterative process in which they inputted their ideas about interactions among proteins within cells to the computer system that, in turn, considered their thinking and used advanced calculation techniques to generate a set of results. The researchers analyzed these results and entered new ideas into the system, which then responded with a new round of analysis and results. In essence, the researchers engaged in a type of brainstorming session with AI to evaluate and advance ideas. In doing so, they improved the decision-making process by incorporating not only these impressive AI capabilities but also expert human intuition (Prabhakar, 2017).

(*continued on next page*)

Table 1 (*continued*)

	In an attempt to build a more efficient and responsive supply chain, Intel is seeking to use AI to assess and manage its supplier relationships. Some of the functions of the AI system include monitoring supply disruptions and reputational risks as well as finding potential new suppliers. Although the tech giant expects most of the analysis to be seamless, the company understands that some of the supplier evaluations and sourcing decisions will be complicated and will require human involvement in the decision-making process. Therefore, the system is reliant on both humans and AI (Saenz et al., 2020).

& Sadler-Smith, 2013Akinci & Sadler-Smith, 2013). Even though AI is not influenced by emotion and therefore is not biased in a human sense, an AI can only base its decisions on the data to which it has been exposed. There is therefore an indirect bias in AI decision-making because it does not account for information that was not entered into the system. For example, Amazon aborted an AI-based recruiting model that was developed to identify promising candidates because it was biased against women. As the computer model was trained on resumes received by the company in the preceding 10 years, the model automatically favored male applicants owing to the male dominance in the tech industry during that time (Dastin, 2018). As a result, the system discriminated against female candidates.

Another AI issue that is similar to human intuition is explainability. Because intuition is an unconscious and automatic process (Dane & Pratt, 2007), humans often struggle to explain how they came to an intuitive decision. They are unable to articulate the decision-making process or to clearly explain the factors they considered in making the decision. Likewise, a decision derived by a multilayered machine-learning algorithm based on weighted combinations of a myriad of factors is difficult to explain (Tambe et al., 2019). This lack of explainability not only gives rise to skepticism and fairness concerns but also hinders organizational learning and development, as the processes involved in making decisions remain mysterious.

Overall, an advantage of AI is that it is objective and impartial since it is unhindered by social considerations. But the lack of social and emotional intelligence can also be a disadvantage, as human emotions play a pivotal role in organizational success or failure. On the other hand, human intuition can be flawed because of biases and the human inability to process large amounts of information. Therefore, relying on either technique alone seems less than optimal for organizational decision-making. In fact, underestimating the value of integrating intuition and expertise with algorithmic capabilities has been found to lead to application failures and missed learning opportunities for organizations (Saenz et al., 2020; see Table 1 for examples of some risks associated with AI overdependence without human collaboration).

Consequently, to improve organizational decision-making, it seems prudent to combine both expert intuition and AI in making decisions. For example, in a research study involving 1,500 companies, Wilson and Daugherty (2018) found that organizations achieve the most significant performance improvements when humans and AI collaborate (see Table 1 for some examples of successful AI and human collaboration). The question is: How can decision makers combine their intuitive expertise with AI to make effective decisions in today's complex and ill-defined organizational environments?

8. Integrating AI and intuition

Scholars have suggested that one way to enhance the collaboration between human intuition and AI is for each to focus on different types of decision tasks. Owing to its high analytic capabilities, AI can focus on complex analytical tasks, whereas humans can focus on tasks with uncertainty and equivocality (i.e., ambiguous decision situations that can lead to divergent interpretations). However, according to Jarrahi (2018), even the most complex analytical tasks may have elements of uncertainty and equivocality, which highlights the importance of human involvement in such decisions. Therefore, it may not be optimal to assign a decision-making mode solely based on the type of task.

In this article, I argue that the effectiveness of collaboration between human intuition and AI for decision-making is dependent on two main criteria: the expertise of the human decision maker (an individual characteristic) and the properties of the task (a task-related characteristic). As previously noted, intuition is only effective when the decision maker is a domain expert and when the task is ill-structured. Therefore, human intuition in combination with AI will only be useful when both of these conditions are met. If the decision maker is a novice, it may be prudent to delegate decision-making authority to AI regardless of whether the task is structured or not, since the novice will not have the capacity to supplement or correct a decision derived through extensive computation. Likewise, if the task is structured and an accurate decision can be derived through logical analysis, the decision should be delegated to AI because not even expert humans can match the speed and analytic capabilities of computer systems.

Assuming the two necessary conditions are met, how should decisions be made? Figure 1 presents a decision-making model with two different sequential approaches to combining intuition and AI. The first approach, termed the confirmatory method, is when the decision maker first makes an intuitive judgment and then uses AI to either confirm or change the initial decision. The second approach, termed the exploratory method, is when the decision maker first uses AI to identify potential decision options and then decides on the basis of intuition.

8.1. The confirmatory method

In the confirmatory method, the expert decision maker first makes an intuitive judgment relating to a particular task or business problem. Through this method, the decision maker identifies one or more alternative approaches to tackle the issue at hand. Then, AI methods are used to evaluate the approaches identified by the decision maker. If the decision maker's intuitive decision is confirmed by AI, then action should be taken to implement that decision. But if the AI analysis contradicts the intuitive decision, or if the results are inconclusive (i.e., if the AI does not confirm or contradict the intuitive decision), then two courses of action can be taken depending on the time sensitivity of the business problem. Ideally, if more time is available to make a decision, the decision maker should consider other options and reevaluate those decisions using AI until a satisfactory decision is reached. If under extreme time pressure, then the expert decision maker should go with their intuitive decision, as intuitive decisions have been found to outperform analytical methods for ill-structured tasks when the decision maker is an expert (Dane et al., 2012).

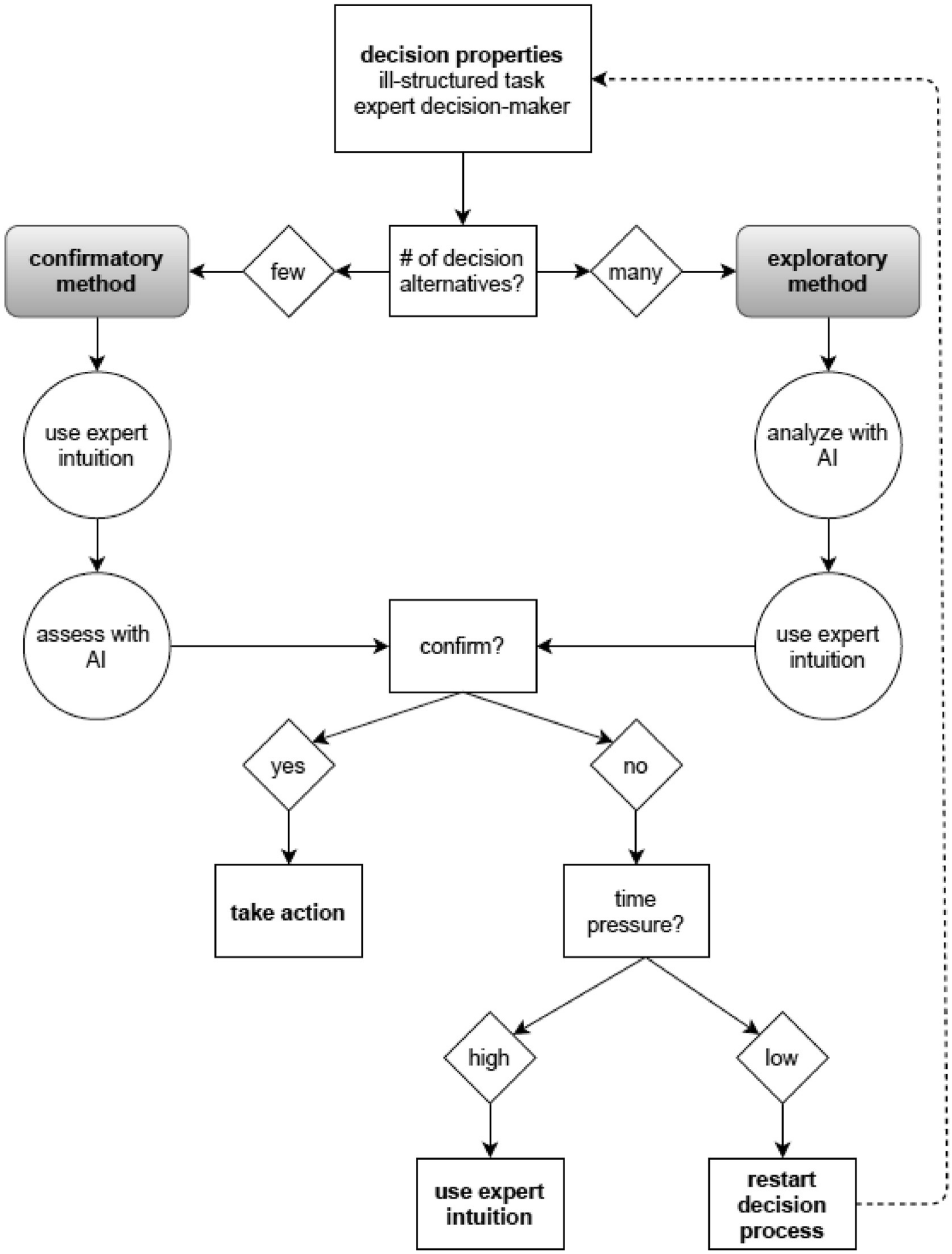
The confirmatory method is most useful in situations in which there are a limited number of decision alternatives. To illustrate this decision-making process, let us consider a fourth-down conversion attempt in the game of American football. In this ill-structured decision-making context (owing to outcome uncertainty), the offense (the team with the ball) has one last attempt to advance the ball beyond the first-down marker that would allow the offense to keep the ball. If the offense does not progress beyond the first-down marker, the other team will get the ball and gain field position. As fans of American football know, this is usually a pivotal point in a game that could well determine the outcome.

When faced with this problem, the coach of the offense (i.e., a domain expert) has two main decision alternatives (i.e., limited decision alternatives: to go for the fourth-down conversion or to kick the ball. The coach could intuitively decide to go for the conversion and then check with their analytical team to assess the probability of success, which often is derived through AI-based complex computational techniques using past data. Major-league sports teams across the world often employ AI-powered advanced sports analytics software to aid decision-making. If the analytics confirm the coach's intuitive decision, then the decision is implemented. However, if the analytics contradict the coach's decision or are inconclusive, then the coach must decide to go either with their gut or with the analytical data. This decision usually must be made within a matter of seconds. Since there is no time to reevaluate options, the coach's best choice is to go with their gut feeling. Even though the AI algorithms likely considered thousands of similar decision situations and a multitude of other factors, the coach has a unique advantage because they are more familiar with the current game situation. For example, the coach can sense the confidence and the energy level of the players, which the analytics would not have considered.

8.2. The exploratory method

In the exploratory method, AI is first used to identify a set of decision alternatives, which are then evaluated by an expert decision maker. This method is best for situations that have many decision alternatives, as AI can narrow the decision options and provide a few possibilities for the decision maker to choose from. This reduces the mental strain on the decision maker and minimizes decision flaws caused by an individual's inability to process large amounts of data. If the human decision maker's intuition confirms the decision derived through AI, then the decision is implemented. If not, as with the confirmatory method,

Figure 1. **Integrative intuition-AI decision-making model**



the decision process should be restarted until a satisfactory decision is arrived at. However, if under extreme time pressure, then the expert decision maker's intuitive judgment should take precedence over AI for the reasons previously noted.

An example of the use of this method would be selecting an employee for a complex job. Hiring for a complex job (e.g., executive-level positions) can be an ill-structured task, as it is often difficult to set accurate evaluation standards for hiring owing to the difficulty in determining which characteristics lead to successful job performance (Chen et al., 2008). In this situation, AI can be used to narrow down the candidate pool to a few candidates, and then expert judgment can be used to select the best candidate. In another example, a medical doctor can use AI to diagnose a medical condition and then rely on their expert judgment to decide on the best course of treatment.

9. How does the model augment organizational decision-making?

This model extends existing frameworks that attempted to combine humans and AI in organizational decision-making. For example, Shrestha et al. (2019) proposed a framework that includes an AI-to-human (AI decisions as input to human decision-making) and human-to-AI (human decisions as input to AI decision-making) sequential decision-making process. An AI-to-human decision-making sequence is suitable when there are many decision alternatives and the specificity of the decision search space is high in the first phase and low in the second phase. The authors argued that AI algorithms are effective in a decision search space that can be well specified (i.e., well structured). Humans, on the other hand, can accommodate a loosely defined decision space. A human-to-AI sequence is best when there are a small number of decision alternatives and the decision search specificity is low in the first phase and high in the second phase. In both sequences, decision speed and replicability of the process are adversely affected by human involvement.

The hybrid process proposed by Shrestha et al. (2019) emphasizes important considerations for managers in decision situations that have a combination of well-structured and ill-structured decision environments. AI is used for the structured component, and humans are used for the unstructured portion. But their framework does not propose a specific strategy for predominantly ill-structured decision environments, a type of environment that is common in today's novel and dynamic business settings. To this end, the model presented in this article outlines a process to make decisions in ill-structured decision contexts. Furthermore, the present model emphasizes the role of expert intuition, a factor that was not considered by Shrestha et al. (2019). As previously noted, both task-related and decision-maker-related factors must be considered when integrating humans and AI. Lastly, when the appropriate conditions are met, the present model provides guidance on how to make decisions when humans and AI disagree on the best course of action.

It is important to note the iterative nature of this model. Barring extreme time pressure, if humans and AI disagree on a decision, the decision options should be reevaluated. In certain situations, it may be useful to follow a different decision path than what was initially used. For example, because of the uncertain and evolving nature of many ill-structured problems, a business problem that was initially thought to have a few decision alternatives may have other decision options that the decision maker had not considered. Therefore, if the confirmatory method did not produce a satisfactory result (i.e., a human decision that was confirmed by AI), then using the exploratory method may unearth some options that were previously overlooked.

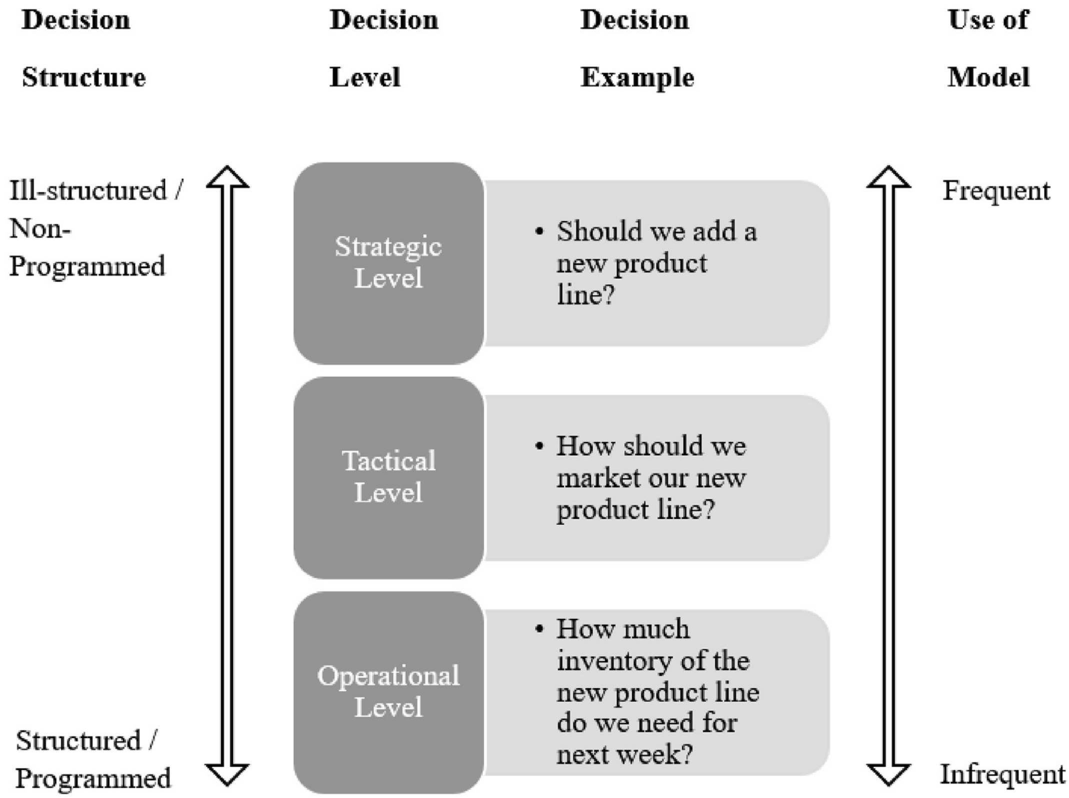
10. Implementing the model for organizational decision-making

As previously noted, the effectiveness of this model is predicated upon two key factors: the expertise of the decision maker and the presence of ill-structured tasks. Therefore, when using this model to make organizational decisions, it is important to ensure that both conditions are met. With regard to the decision maker's expertise, research suggests that it may take 10 years of intense experience for an individual to achieve expertise in a particular domain (Dane & Pratt, 2007). However, there is some indication that individuals may be able to make effective intuitive decisions with a moderate level of experience (e.g., Dane et al., 2012). The time it takes to achieve expertise may vary based on the profession and should not be measured by years of experience alone; both the breadth and depth of knowledge should also be considered.

Regarding the structure of the problem, if a precise solution can be derived through analytical processes such as computation, then such methods should be used to resolve the issue. But when decision cues are vague and there is ambiguity surrounding the best course of action, then the model presented in this article guides an expert decision maker, in combination with AI, to make effective decisions. In essence, the model is not necessary for programmed decisions (i.e., recurring decisions where decision rules have been established) but will be useful for nonprogrammed decisions (i.e., infrequent decision scenarios where decision rules have not been established). Importantly, the counterbalancing effect of having both humans and AI in the decision-making process minimizes the risk of making a poor decision.

The framework can be useful for all levels of organizational decision-making. As depicted in Figure 2, the use of the model will vary depending

Figure 2. Use of integrative intuition-AI decision-making model by decision level



on the decision level. At the lower level (i.e., operational level), most decisions are routine and typically fall into the programmed decision category. As such, these types of decision environments are often well-structured, where decisions are arrived at through well-established decision rules. Since AI-based systems will be more efficient than humans in making such decisions, the integrative intuition-AI decision-making model may not be frequently required at this level. At the tactical level, where medium-term decisions are made to achieve strategic goals, the model becomes more useful as the decision environment becomes less structured and managers must incorporate their expert judgment to make decisions. At the strategic level, senior managers make complex decisions in often ill-structured decision environments. Strategic decisions, such as which market to enter or which business to purchase, typically are marked by uncertainty and ambiguity. Therefore, at this level, the model can be more frequently used to make decisions.

The usefulness of the model should be assessed for both efficiency and effectiveness using a combination of quantitative and qualitative measures. Table 2 presents some examples of such measures that could be used for this purpose. Using a variety of metrics would allow a more comprehensive assessment of the model.

11. Implications for managers

In this article, I have discussed important aspects of intuitive and AI-based decision-making. Although both forms of decision-making have unique advantages, each method also has weaknesses that restrict the quality of decisions derived through one method alone. Therefore, instead of pitting intuition against AI and trying to identify which technique is better, the most prudent course of action is to identify the optimal way to combine these two methods to increase overall decision effectiveness. To this end, this article presents a model that specifies a decision process in which both intuition and AI can be used in combination. The model is based on the premise that combining intuition and AI will only be effective when two conditions are met—that is, when the task is ill-structured and when the decision maker is a domain expert. If either of these conditions is not met, it will be best to use AI.

Table 2. Measuring the efficiency and effectiveness of the model

	Quantitative measures	Qualitative measures
Efficiency	• Speed How quickly are decisions made using the model compared to other decision-making methods? • Cost How much does it cost to make decisions using the model? Is it more cost-efficient compared to other methods? • Frequency How often is the model used for decision-making?	• Ease of use How easy is it to use the model? • Collaboration Does the model facilitate efficient collaboration among decision makers?
Effectiveness	• Success and error rate How often are the right and wrong decisions made using the model? • Return on investment What is the return on decisions made?	• Buy-in Do others agree with and support decisions made using the model? • Fairness perceptions Are the decisions perceived to be fair?

The use of one of the two decision methods specified in this article (i.e., the confirmatory method or the exploratory method) will primarily depend on the number of decision alternatives available in the decision context. When the decision alternatives are limited, the confirmatory method enables the decision maker to make a quick decision based on their expert intuition, and then to use AI to evaluate the choice. In this method, AI functions as a check on expert intuition and reduces the effect of decision maker bias, which is a major flaw attributed to intuitive decision-making.

Conversely, when there are many decision alternatives, the exploratory method narrows the decision alternatives with the use of AI, and then the decision maker uses their expert intuition to select the best course of action. In this method, AI reduces human decision flaws that are attributed to information overload. In both methods, combining AI with human decision-making reduces the vulnerabilities of AI, such as interpersonal and ethical considerations, negative employee reactions to decisions made by algorithms rather than humans, and unique events for which there are insufficient past data to train algorithms to predict future events effectively. Overall, the two decision approaches presented in the article attempt to maximize decision quality while minimizing the inherent weaknesses of each technique alone.

In addition to improving decision quality, on a larger scale, combining AI and human decision-making is a step toward easing the growing societal concern that machines will take over human jobs. Finding ways for humans and AI to work together will make humans feel less threatened by AI and more willing to work with it. While there is little doubt that the future of human work is changing and will be significantly reshaped by technological advances such as AI, human input will still play a pivotal role in organizational decision-making. Therefore, the more collaboration that can be cultivated between human workers and AI, the more useful AI will be in advancing organizational processes.

At the same time, organizational decision makers should be cautioned regarding the downsides of overreliance on AI for decision-making. For example, consider the impact on medical practice, a profession that has seen a significant uptake of AI. Some of the concerns of AI integration in the field include decrease in physician-patient engagement, reduction of physician compensation caused by a decrease in relative value, and the risk of skill erosion in diagnostic expertise and clinical judgment (Miller & Brown, 2018). Similar concerns surrounding AI abound in other industries as well. Therefore, it is critical to strive to find the right balance between the use of AI and human skills in organizational processes.

AI can be effective in improving group decision-making as well. In the past, group decision-making was one strategy often prescribed to reduce individual biases in intuitive decision-making (Miles & Sadler-Smith, 2014). In some cases, group decisions have even been found to outperform AI-based decisions (Metcalf et al., 2019). But various factors, such as information exchange barriers, often limit the effectiveness of group decisions (Dennis, 1996). "Artificial swarm intelligence" (Metcalf et al., 2019) is an AI-based technique that could potentially alleviate not only the human deficiencies in the group decision-making process but also some key limitations of AI, such as its lack of tacit knowledge and its reliance on historical data. This novel technique enables geographically dispersed human groups to work together in real time, using a dynamic platform, to navigate a decision space collectively and to converge on a decision (Rosenberg, 2016).

A limitation of the decision-making model introduced in this article is that it may not readily address a common flaw attributed to both human intuition and AI, which is the lack of explainability. The inability to explain the decision-making process adequately invites concerns over justice and fairness. For example, in HR, hiring and firing decisions usually have a significant impact on individuals and communities, which raises concerns of ethical practice, fairness, and procedural and distributive justice (Tambe et al., 2019). These concerns will intensify if the decision-making process cannot be clearly described. Also, the lack of explainability significantly hinders organizational learning and development. When the decision-making process cannot be explicitly stated, the process cannot be developed as a prototype or a decision aid for future decision-making. We can hope that developments in explainable artificial intelligence (Guidotti et al., 2018) will help to alleviate this issue, but organizational decision makers need to be aware of the consequences of this limitation.

This model may not be as useful in completely novel business situations. This is because both human intuition and AI draw on existing knowledge to form a judgment: intuition draws on experience and AI draws on data input. When no prior knowledge structure can be used to understand and form a judgment in a new situation, then both intuition and AI become less effective. For example, certain disruptive events, such as the COVID-19 pandemic, may completely shift the business landscape such that prior knowledge about a particular business environment may not be as useful in making future decisions. Decision makers must be cautious in using this model in such circumstances.

12. Future research considerations

Given the increasing integration of AI in organizational decision-making, it is important for both industry and academia to better understand not only the impact of AI on the decision-making process but also how best artificial and human intelligence can be combined to optimize organizational performance. As a step in this direction, the model presented in this article specifies two decision-making processes to combine AI and human intuition, depending on the properties of the decision environment. As a next step, this model should be empirically tested. There may be other organizational or individual factors that may affect AI-intuition collaboration. For example, will younger, more tech-savvy managers be more willing to use AI in combination with their intuition than older managers, who are more used to relying solely on their intuition? Will younger managers rely too much on AI and not enough on their judgment?

Another important area of research is to better understand the ethical implications of AI in organizational decision-making. How will AI respond to ethical dilemmas? Consider the ethical dilemma illustrated by the familiar runaway trolley experiment, a binary decision context in which one alternative leads to the death of many and the other choice leads to the death of one. Will AI sacrifice the many for the benefit of one? Or will AI save the many by sacrificing the one? Imagine an automated car with one passenger (the owner of the vehicle) driving on a cliffside road. Suppose the car has a malfunction, and the only options are either to drive over the cliff, which will most certainly kill the passenger, or to drive into a crowd of five, likely killing all of them but saving the passenger from certain death. How will the AI-based automated vehicle react? Will it be loyal to the owner and save the owner's life at any cost? Or will it aim to do the greater good (i.e., to minimize loss of life) by sacrificing the car owner? Many organizational decisions can affect the lives of stakeholders and even the larger community, so business managers need to recognize the impact of AI from an ethical standpoint.

Relatedly, the impact of AI on justice perceptions is another important area of research. As previously noted, people may be less trusting of decisions derived through algorithms than those made by humans, especially when those decisions have an adverse impact on them. Owing to the lack of explainability of AI-based decision-making, there may be concerns about procedural and distributive justice (Tambe et al., 2019). There is insufficient empirical research for anyone to truly understand the impact of AI-based decision-making on justice perceptions. Will combining AI with human intuition add to or alleviate these concerns? What steps can organizations take to reduce negative perceptions related to the use of AI?

Answers to such questions have important implications for the successful adoption of AI in organizational decision-making.

AI regulation is another critical area of research. As the role of AI in organizational decision-making continues to expand, how best can AI be regulated to minimize harm to humans and to hold organizations accountable for their actions? Haenlein and Kaplan (2019) argue that instead of regulating AI systems, a better way is to develop commonly accepted requirements related to the training and testing of AI algorithms. Given the rapid change in AI technology, the authors argue that this method would enable stable regulation even if the technology changes over time. By identifying effective ways to regulate AI, academic research can immensely contribute to the healthy integration of AI in organizational processes.

13. Conclusion

The decision-making model presented in this article is an integrative one that combines the strengths of expert intuition and AI to solve ill-structured organizational problems. In a fast-changing environment where AI has transformed organizational processes, the model identifies an effective way to combine complementary skills of the two modes while minimizing the vulnerabilities of each method. Throughout history, human intuition has had an extraordinary impact on innovation and advancement, including too on the creation and development of AI. Therefore, rather than attempting to replace this unique human skill with advanced technology, organizations will greatly benefit from the integration of intuition and AI to improve organizational decision-making.

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